CHAPTER C.13
MODEL UNCERTAINTY AND LIMITATIONS

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13.1 Introduction

The models described in this appendix are landmark achievements in collating the extensive scientific and technical knowledge currently available. They were created for the purposes of formulating and evaluating subprovince-level alternative plans (which were comprised of multiple project features) for ecosystem restoration. Although the lack of extensive data sets constrains the models' ability to accurately predict individual project benefits over 50 years, the conceptual frameworks developed for the models are sound and represent the best available scientific understanding of ecosystem function. Even though precise project benefits over 50 years could not be predicted, the PDT was able to compare the relative effectiveness of alternative subprovince plans. They could also distinguish between these plans with reasonable certainty that the most cost-effective and ecologically beneficial alternatives were being considered. Further, these models represent the most objective and powerful predictive tool at the subprovince scale available to resource managers at this time.

Output provided by these models assisted the PDT in the determination of 7 cost-efficient alternative plans from which cost-efficient and ecologically meaningful projects could be chosen. The projects that comprised each of the 7 plans were considered in the development of the near-term plan for the Louisiana Coastal Area (LCA) Study. Upon completion, only 13 of the 79 project features considered passed through the selection process for inclusion in the near-term plan. Of those 13 projects, only 5 are being recommended for programmatic authority for construction. These 5 have been selected because they have significant value in addressing critical ecological needs, they have some level of planning and design already completed, and because they will utilize technology which has already been proven to be cost-efficient and ecologically beneficial by similar projects implemented under other Federal and State programs. This is also consistent with the Adaptive Environmental and Assessment and Management (AEAM) process, described elsewhere in this report, wherein the design of future actions is built upon lessons learned regarding the efficacy of past restoration actions.

Uncertainty is inherent in ecosystems, and is therefore unavoidable when managing large-scale ecological systems. Thus, assumptions must be made when creating predictive ecological tools. As acknowledged above, the lack of extensive data sets for all parameters being considered creates further uncertainty in the models' ability to accurately predict benefits over the 50-year project life. Acknowledging and identifying these and other uncertainties is critical for the most appropriate utilization of output. It is the consensus of the scientists who created these models that the outputs are a sound basis for decision making at the subprovince scale.

As the LCA Program proceeds, these subprovince-level models will continue to be developed and – where possible – uncertainty will be reduced through the Science and Technology Program. This is an integral step in the LCA AEAM program, and it allows for large-scale ecosystem restoration to proceed even as researchers work to further reduce those uncertainties.

In the context of a coastal restoration effort, model uncertainty can be defined as the deviation of model predictions from the actual response of the ecosystem to a certain restoration project. Uncertainty is caused by natural variability (temporal and spatial), lack of data with sufficiently high quality and resolution, gaps in theoretical knowledge, and uncertainty of model algorithms and parameters. Perhaps a major challenge facing the Louisiana Coastal Area (LCA) Ecosystem Restoration plan lies in the inherent uncertainty of how well a proposed restoration effort will work. This is particularly relevant for the LCA plan since it depends on the results of a complex suite of hydrologic and ecological simulation models. Given the physical complexity of the Louisiana coastal systems, the predictive abilities of such models are far from perfect. In reality, these models provide an approximation of what takes place in the Louisiana coastal system. Hydrodynamic, hydrologic and ecological models quite often have coarse spatial and temporal resolutions relative to scales over which physical processes actually take place. Climatic, hydrologic, and ecological data used as model inputs and boundary conditions are usually available at limited spatial and temporal sampling resolutions. Thus, it is recognized that the predictions of such models are associated with uncertainties.

Predicting the effect of restoration measures on ecological processes and ecosystem structure is further complicated by the fact that uncertainties propagate in a nonlinear manner through the sequentially used hydrologic and ecological models. As a result, uncertainties will always exist at different project levels and scales and will inevitably impact the decision making process. There is a critical need to estimate and quantify these uncertainties and their impact on the performance measures that are used to assess specific restoration alternatives. This objective can be achieved by formulating a comprehensive uncertainty analysis (UA) framework. In this framework, all possible sources of uncertainty are identified, the marginal and joint probability distributions of the uncertain input variables and parameters are specified, and specific uncertainty analyses scenarios and computational techniques and algorithms are specified and applied.

The development of an uncertainty framework is initiated by systematically identifying the sources of uncertainty in each of the modules developed in the context of the LCA comprehensive ecosystem restoration plan. Given the complexities of the different modules involved in the Louisiana coastal system project, and the amount of physical and computational time needed, it is recognized that formulating and implementing the complete framework is beyond the scope of the proposed task. Instead, and in the short term, this task will focus on some feasible aspects of the uncertainty analysis problem that will eventually help in formulating a long-term strategy for quantifying, reducing, and communicating model uncertainty to decision makers. The activities and findings of this task will be beneficial for the development of an adaptive management framework and the long-term environmental monitoring programs.

The general objective of this task was to identify the degree of uncertainty of the parameters and variables used by each of the modules. This objective facilitated the identification of different levels of uncertainties in the statistical and numerical models and their impact on the evaluation of the different management scenarios as established in the LCA ecosystem model report. This chapter includes 1) a general review of uncertainty analysis (UA) in the context of ecosystem restoration and establishes a framework for the definition of the uncertainty concept appropriate for use in future analyses for coastal Louisiana., 2) a review and evaluation of the types of uncertainty analyses which have been performed to date for each module, 3) identification and analysis of the dominant sources of uncertainty (data, input variables, and model algorithms and parameters) in each module.

13.2 Uncertainty Analysis, Concepts, and Terminology

The first step in quantifying risk is to identify the sources of uncertainty. Risk is the probability that a hazardous outcome will occur and the consequence of uncertainty: if there is not uncertainty, the concept of risk is irrelevant because the probability of the outcome is 1 or zero". Risk is an inevitable consequence of the uncertainties that are inherent in our knowledge of ecological systems, and ecologist must develop rigorous methods for evaluating these uncertainties (Harwood and Sotkes 2003). However, uncertainty is a critical term that can be interpreted differently depending on the discipline and context where it is applied (NRC 2000). In the most simple definition uncertainty is defined as "incomplete information about a particular subject", where ignorance is considered as an extreme form of uncertainty (Hardwood and Stokes 2003). Applied to the environmental sphere, it can be understood as "the long-term consequences that economic and human activities may have on the environment or health but that the present state of science does not enable us to foresee (Webster dictionary)". However, natural systems are not only affected by human activities but also by large natural disturbances (e.g., hurricanes) that operate at large spatial scales and have tremendous effect on the structure and function of entire ecosystems. Although there is a large literature on scientific uncertainty, ecological uncertainty has not been well described (Ludwing 2001). The lack of formal analyses of uncertainty of large scale restoration projects is badly needed to be able to differentiate uncertainties that are inherent of natural processes ("naturally variability") and those that are the result of incomplete knowledge.

The scheme proposed by NRC (2000) was modified to analyze the different sources of uncertainty for each the LCA modules. This scheme was originally proposed to analyze the uncertainty in water resources project planning, particularly flood damage (Figure C.13-1). The basic definitions and components associated to each term presented in Figure C.13-1 are given below. For further discussion about each of terms the reader is directed to the work by NRC (2000), Lall *et al* (2002), Harwood and Strokes (2003) and Ludwig *et al* (2001).

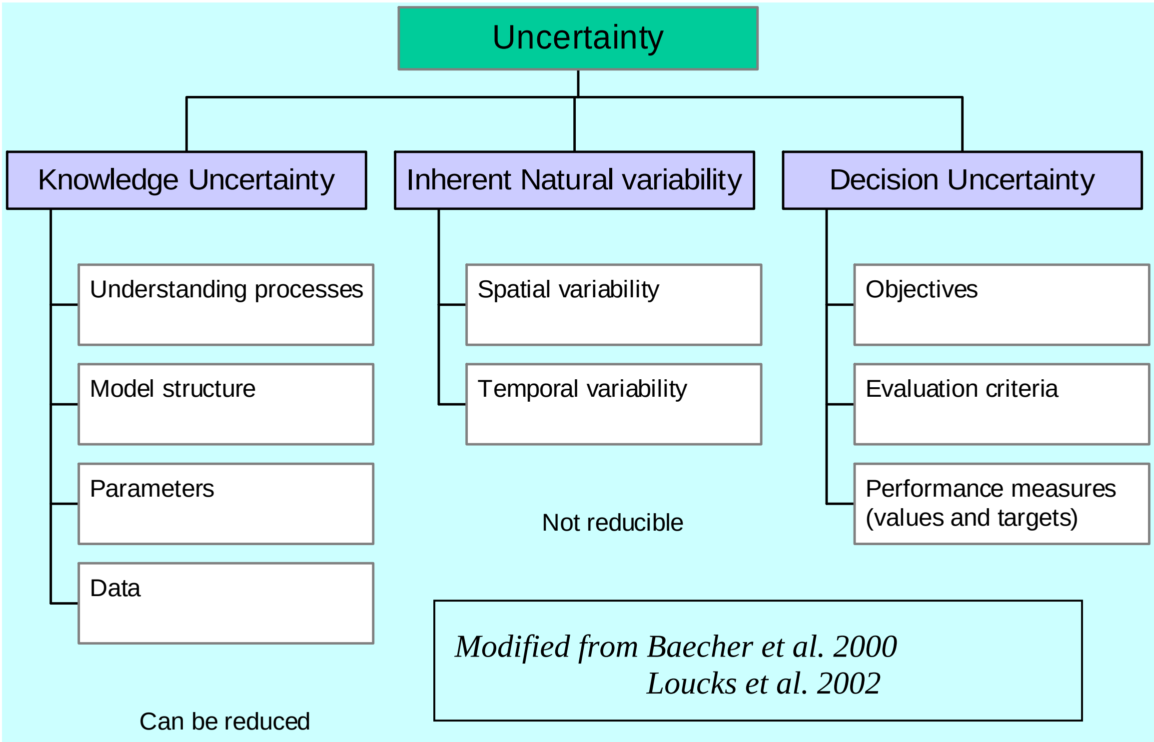

Figure C.13-1 Description of the uncertainty in risk analysis in environmental problem solving and decision making based on natural variability, knowledge uncertainty and decision model uncertainty.

13.2.1 Knowledge uncertainty

This type of uncertainty refers to the lack of understanding of events and processes. It is associated to a lack of data from which to obtain inferences. Because this uncertainty is related to the "state of the art" in knowledge about different processes, it can be reduced as more information is gathered. Knowledge uncertainty can have four components: understanding of processes, model structure, parameters, and data.

A. *Understanding processes*. It is strongly related to the limits of scientific understanding, such as what knowledge is lacking or what temporal or spatial scale mismatches exist among disciplines. This type of uncertainty is closely related to the "structure of knowledge" discussed by Benda *et al*. (2002). These authors include the following categories, which limit our understanding of phenomena across different disciplines: a) disciplinary history and attendant forms of available scientific knowledge, b) spatial and temporal scales at which that knowledge applies, c) precision (i.e., qualitative versus quantitative nature of understanding across different scales, d) accuracy of predictions; and e) availability of data to construct, calibrate, and test predictive models.

B. *Model structure.* Refers to the degree to which a chosen model accurately represents reality. Uncertainty arises from the use of surrogate variables, the exclusion of variables, and from the approximations and the use of the incorrect mathematical expressions for representing the physical and biological world (NRC 2000). To select the best management strategies, models of the underlying biological processes that take account of the best scientific knowledge and the uncertainties associated with this knowledge need to be available to test the robustness of different management strategies. (Harwood and Stokes 2003).

C. *Parameters*. This component is closely related to the accuracy and precision with which parameters can be inferred from field data, judgment, and the technical literature. Parameter uncertainty derives from statistical considerations; it is usually described by confidence intervals (frequentist, statistical models), or by probability distributions (Bayesina statistical models).

D. *Data*. Uncertainties associated to this category are the principal contributors to parameter uncertainty, including a) measurement errors, b) inconsistent or heterogeneous data sets, c) data handling and transcript errors, d) non-representative sampling caused by time, space, or financial limitations.

13.2.2 Inherent natural variability uncertainty

This type of uncertainty is also referred as external, objective, random or stochastic. It is related to the inherent variability in the physical world and considered as irreducible. This type of variability is critical in management decisions since it is usually poorly understood and confused with uncertainty as result of "ignorance" (knowledge uncertainty) by managers, lawyers, and stakeholders (Rose and Cowan 2003).

13.2.3 Decision uncertainty

This category includes uncertainties resulting from our failure to understand how alternative projects or designs should be evaluated and the social and economical context where management decisions are made. This uncertainty is also strongly related to the way model predictions are interpreted and communicated. When high uncertainty is not properly explained or understood, it can delay action or cause the selection of values at the "extreme of the ranges that result in highly risky (or overly conservative) management decisions (Frederick and Peterman 1995, Rose and Cowan 2003).

13.3 Uncertainty Analysis Techniques

There are number of computational techniques that can be used for uncertainty analyses. Detailed description of such techniques is beyond the scope of this report. Instead, only a brief discussion is provided and the reader is referred to literature on statistical and uncertainty analysis.

13.3.1 Analytical methods

This approach can be used to construct distribution of model predictions in situations with a limited number of random variables and parameters are considered. It also requires that the model is rather simple and can be analytically traced. Apparently, this technique is not applicable to the *LCA* model which involves large number of parameters and variables. The multiple modules that are encompassed within the *LCA* model also make it difficult to perform an analytically based uncertainty analysis.

13.3.2 Random Sampling: Monte Carlo and Latin Hypercube methods

This approach is based on the assumption that all the uncertain model parameters and input and output variables are random variables. It is also assumed that the marginal and joint probability distributions of these variables are known. Such distributions are used to generate realizations of the uncertain model variables. The generated values are then used to perform model simulations and produce the desired predictions. This process is repeated many times (typically few hundreds). The repeated simulations can then be used to construct a probability distribution of the model output. Figure C.13-2 shows a schematic illustration of this simulation-based technique.

Given its stochastic nature, the Monte Carlo random sampling appears to an appropriate methodology to perform uncertainty analyses for the *LCA* model predictions. However, there exist some limitations on applying this approach. One major limitation is the large number of model simulations that might be required to construct reliable probability distributions. A modified sampling technique known as the Latin Hypercube Sampling method can be used to improve the computational efficiency. Another limitation is due to the possibility of existence of correlation among the different random variables that are considered. In such situations, conditional distributions of the correlated parameters need to be specified which is not always easy to achieve.

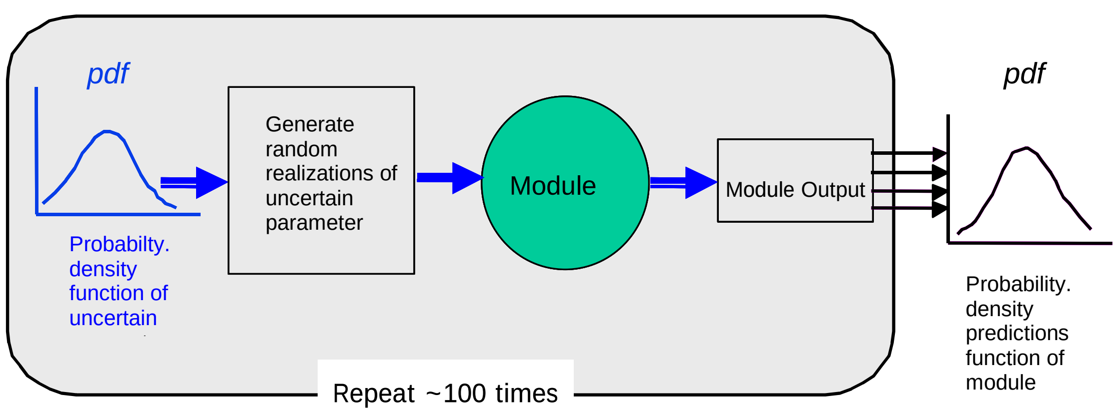

Figure C.13-2 Illustration of the Monte Carlo simulation method for model uncertainty analyses

13.3.3 Bayesian approaches

This approach builds on traditional Monte Carlo methods and uses Bayesian inference to combine prior information of the model input uncertainty with the ability of different parameter sets to describe observed data. Further details about this approach are available several references (e.g., Dilks et al., 1992; Song et al., 2003).

13.3.4 Generalized Likelihood Uncertainty Estimation (GLUE) method

The GLUE technique has been developed and proposed by Beven (2001a) for performing uncertainty analyses of model predictions. Details of this approach and its applications can be found in numerous studies on hydrological modeling analyses (Borga, 2000; Beven 2001b; Refsgaard and Storm, 1996).

13.4 Sources of Uncertainty in the LCA Ecosystem Model

This section discusses and identifies the main sources of uncertainty in the different LCA modules in accordance with the scheme defined in section 13.2. To classify the model and parameter uncertainties, three categories of scientific rigor were used:

- High: Based on extensive scientific literature
- Moderate: Some data available on the relationship between the output variable and the driving forces, but this relationship needs to be strengthened with additional research
- Low: Primarily based on professional judgment

Parameter quality was also categorized in three categories:

- High: Based on extensive data sets
- Moderate: Some data available or based on well developed predictive models
- Low: Primarily based on team's professional judgment or based on unrefined predictive models

13.4.1 Sources of uncertainty in the Water Quality Module.

The water quality module (WQM) generated estimates for N-removal, primary productivity, and chlorophyll concentrations for three of the four sub-provinces considered in the LCA program. These first-order estimates used empirical relationships relating N-removal (Dettmann 2001, Seitzinger 2001), chlorophyll a concentrations (Boyton 1996), and primary productivity versus N loading rate and water residence time (Nixon 1996). Since these relationships were obtained from statistical relationship, which include a large variety of coastal ecosystems in the USA and other sites around the world, there are potentially several sources of uncertainty.

Descriptions of the different sources of uncertainty associated to the models used to estimate all variables in the WQM are given below. Table C.13-1 provides an overview of uncertainties in the WQM.

Table C.13-1. Overview of Water Quality Model Uncertainty.

Environmental Driver or Factor	Model Rigor	Data Source	Parameter Quality
Water Residence Time	Moderate	Hydrodynamic desktop model	Low
Basin Bathymetry	Moderate	Hydrodynamic desktop model	Low
Wetland Area	Moderate	Land Change Module	Low
Water Depth	Moderate	Land Change Module	Low
Temperature	Moderate	Hydrodynamic desktop model	Low
Salinity	Moderate	Hydrodynamic modules	Low

Knowledge Uncertainty.

A. *Understanding processes*.

Denitrification, algal bloom formation (phytoplankton dynamics) and N uptake by plant communities across coastal Louisiana are some of the most critical processes that need to be understood to evaluate the N removal by wetlands and the water column. Denitrification studies in coastal Louisiana are limited in number and coverage (e.g. DeLaune et al 1998). There is a critical to need to evaluate denitrification at different temporal and spatial scales, particularly in wetland areas where hydroperiod influences environmental factors controlling denitrification (oxygen, NH4 and NO3 supply, etc). Estimates of N removal by the water quality module did not take into consideration actual denitrification rates in both sediments and the water column.

Although algae blooms are a natural processes occurring in coastal and estuarine waters, it is still not clear what are the factors regulating the presence/absence of toxic algae in coastal Louisiana. The recurrent presence of toxic algae is one of the major concerns related to freshwater diversions into regions where water residence time is high. It is not clear at what nutrient concentrations and stoichiometric ratios (e. g., nitrogen, phosphorous, silica) algae blooms become toxic. Studies determining algae composition and species diversity are needed, especially in areas where large nutrient loads are expected as result of changes of local and regional hydrology. These studies need to be designed within the framework of a long term monitoring plan encompassing different habitats. Since primary productivity in the water column in coastal Louisiana is strongly influence by suspended sediments, studies evaluating light quantity and quality and their interaction with nutrient availability are needed. Currently, chlorophyll a estimates in the water quality module does not difference species composition and nutrient requirements by the phytoplankton community.

Nutrient uptake by plants is one of the processes most studied in Louisiana. However, these studies need to be extended into larger scales to account for the variation at the community level. Greenhouse experiments have been valuable in helping to understand the physiological constraints of particular species of plants, yet experiments assessing multi-species level responses are badly needed. Currently there are not comparative studies evaluating nitrogen and phosphorous uptake between marsh and swap species within similar regions. Nutrient uptake rates are necessary to assess how much of the “new “ nutrients into the system are recycled and how much are exported and permanently loss from the system. Evaluating hydroperiod in different types of plant communities is also needed to determine its impact on the export of organic matter into adjacent estuarine waters and denitrification rates in vegetated areas.

B. *Model structure.*

The water quality module does not include mechanistic models, but uses previously published statistical models. The models include N-removal/N-loading relationship for estuaries in general, and for wetland systems (Mitsch et al 2001). The objective was to use these relationships to generate estimates of N-removal, algal bloom potential (chlorophyll a), and aquatic primary productivity. This simplified approach was applied at the scale of entire estuarine systems. Single estimates were developed for each estuarine system and calculations were made for each variable. Each estimate integrates N-loading rates, freshwater water residence time, and wetland-water ratios for the entire estuarine system. The calculations incorporated as much hydrodynamic output as possible, such as salinity, water level, and water depth. Total nitrogen and NO3 loading were estimated using mean concentrations (1983-2000) in the lower Mississippi River (Dubravko 2003). Estimates for N-removal, primary productivity, and chlorophyll a were generated for each alternative restoration scenario provided by the Corps of Engineers in each of the following regions: 1) Subprovince 1, Mississippi East (Breton/Pontchartrain), 2) Subprovince 2, Mississippi West (Barataria), 3) Subprovince 3, Terrebonne, Atchafalaya and Teche/Vermillion

C. *Parameters.*

There are 10 parameters in the water quality module. These parameters were obtained from previously published work and are listed in Table C13-.2.

Table C.13-2. Definition and Values of Parameters Used in the Water Quality Module.

Process	Parameters	Definiton	Unit	Values (or range)	Source
N Removal by the water column	Alpha	first order loss coefficient	Month-1	0.23-0.36	Detmann (2001)
Fraction of N that is denitrified	Gamma	First order coefficient	no units	0.69-0.81	Detmann (2001)
N removal by the marsh surface	Slope	Linear regression (ln) (N03 loading vs % removal)	g-N m-2 y-1	0.45	Mitsch et al 1999)
	Intercept	Linear regression (ln) (N03 loading vs % removal)	% NO3 removal	1.23	Mitsch et al 1999)
N removal by the open water	Slope	Linear regression (ln) (Water residence time vs % N denitrification	Month	9.00	Seitzinger (2001)
	Intercept	Linear regression (ln) (Water residence time vs % N denitrification)	% N denitrified	29	Seitzinger (2001)
Chlorophyll a concentrations	Slope	Linear regression Annual Total Nitrogen load	gN m-2 y-1	0.7	Boynton et al. (1996)
	Intercept	Linear regression Chl concentration	ug L-1	16.9	Boynton et al. (1996)
Primary Production	Slope	Linear regression (ln) (Dissolves Inorganic Nitrogen input vs Primary Production	mol m-2 yr-1	0.442	Nixon et al. (1996)
	Intercept	Linear regression (ln) (Dissolves Inorganic Nitrogen input vs Primary Production	g C m-2 yr-1	2.332	Nixon et al. (1996)

13.4.2 Sources of uncertainty in the Land change module.

Although an attempt was made to make this a process-driven module, the lack of scientific data and the time available for developing this conceptual model forced us to use a combination of empirical relationships and landscape analogs to reflect the complex processes controlling land change in the Louisiana coastal zone. An overview is given in Table C.13-3

Table C.13-3. Overview of Land Change Model Uncertainty.

Environmental Driver or Factor	Model Rigor	Data Source	Parameter Quality
Historical land change	Moderate	Land/water maps	Moderate
Sediment input	Moderate	Mississippi River load (1973-1988)	Moderate
Sediment retention	Low	Wax Lake Delta	Moderate
Bulk density of deposited sediment	High	Natural islands of Atchafalaya Delta	Moderate
Volume of receiving basin	Moderate	Topographic maps and Team's experience	Low
Nourishment (nutrient input and salinity change)	Low	Distance from diversion point and salinity of receiving basin	Low High
Salinity change*	Low	Hydrodynamic desktop model	Low
* *Used in subprovince 4 only*			

<u>Historical Land Change Component</u>

The primary component of the land change model is the historical land change between 1978 and 1990. However, processes that occurred in the past may not occur in the future: specifically, dredging for hydrocarbon extraction and navigation, local subsidence due to fault activation, and the presence of barrier islands, which may affect land loss rates in bay fringing marshes. In addition, a conservative estimate of an error range of 25% for change rate measurements is due to a variety of environmental factors (natural variability) that affect land-water mapping (Barras *et al*. 2003). The land change parameter variability can be reduced by conducting land:water analyses on a greater number of points in time and correlating with existing environmental conditions. Incorporating the changes in processes that affected land change in the past but may have a different effect in the future is extremely difficult and will require a process-oriented model. Currently, spatial explicit data for such a model is lacking. One of the first requirements for such a model would be spatially explicit elevation data as well as subsidence rates that are based on the local geology.

<u>Land Building Component</u>

Land change due to restoration is primarily a result of river diversions that build land through sediment deposition and reduce loss by increasing emergent plant productivity in existing wetlands through increased nutrient availability and salinity stress reduction.

The amount of sediment transported by the different diversions is the most important factor in the land building sub-module. The data on sediment load in the Mississippi River is extensive, however due to time constraints only easily obtainable USGS data were used. The natural variability in load and flow are relatively small at the decadal scale (Figure C.13-3). Examination of the full record and the use of the portion of the record that is most representative of the future trends will improve this data input. The sediment transported by a diversion is a function of the diverted flow, duration and location. In the current model the sediment load is directly proportional to the percentage of the diverted Mississippi River flow. However, this is not always the case. For example, the Wax Lake channel captures 30% of the Atchafalaya flow and 36% of the sediment load (Mossa 1988). The amount of sediment diverted is a function of the depth and location along the river-streambed of the diversion channel (Mossa 1996), but this kind of detail was not examined in this phase of the study. This model uncertainty can be reduced as more detail on each diversion site becomes available.

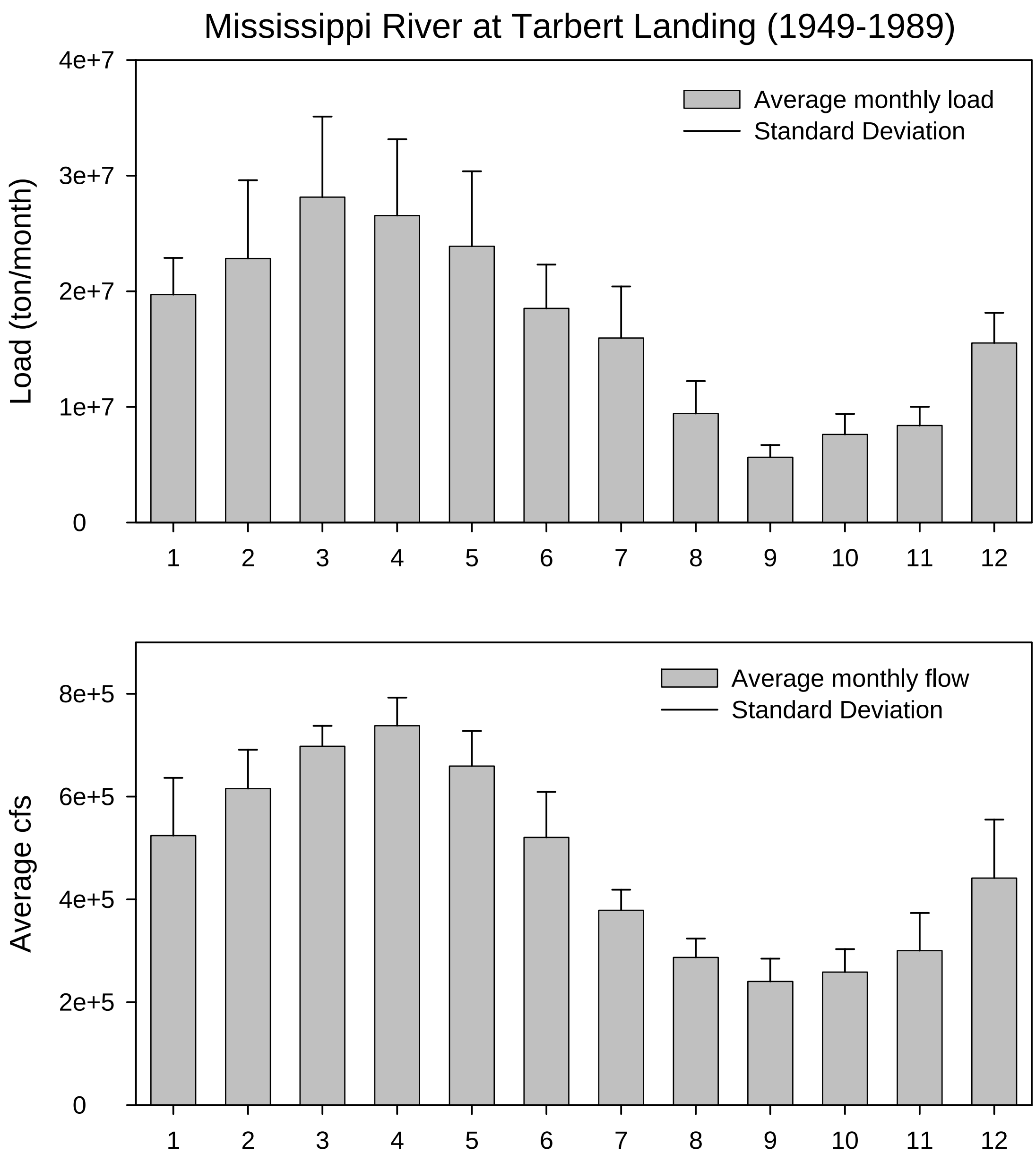

Figure C.13-3. Average total monthly sediment load and flow calculated for 10-year increments, showing the amount of interdecadal variation.

Not all the sediment that is diverted is captured, for example fine sediment particles are often transported offshore. The land building sub-module used a retention rate of 15% based on calibration of the module algorithm to the historical growth of the Wax Lake Delta. This estimate is similar to other estimates for sediment retention rates in the Wax Lake delta (Thomas *et al*. 1982). The knowledge uncertainty for the retention rate is relatively high, because the relationship is based on a best fit under one condition. Additional research examining the effect of receiving basin geomorphology, sediment composition, and exposure to re-suspension forces (wind and waves) to determine their effect on sediment retention is warranted.

Once sediment is captured the module uses the bulk density of deltaic soils to determine the volume occupied. This parameter was based on a few measurements of soil bulk density in the upper 30 cm of the natural islands of the Atchafalaya Delta. Therefore, the parameter uncertainty for bulk density is relatively high. Future models should incorporate bulk density measurements over a larger range of locations and depths. Since bulk density is a direct measurement of the weight of sediment in a given volume of substrate, the model uncertainty can be classified as relatively low.

To determine the change in land surface the volume of captured sediment has to be converted to an equivalent of area of land created. This step uses simple box geometry to convert volume to area. In reality the shape of the receiving area is not a box. The model uses a 2000 coastwide imagery mosaic, which classifies land and water as either marsh ponds or other open water to determine the fill volume available in each cell. The depth of marsh ponds and open water are set based on the team's experience and the average depth of most coastal water bodies on topographic maps. This parameter uncertainty can be reduced with detailed bathymetric surveys of the receiving basins.

<u>Nourishment Component</u>

Diversion effects on existing marshes through nutrient input and salinity reduction (nourishment effect) are based on the two available landscape analogs in the Louisiana coast: Atchafalaya Delta and Caernarvon Diversion. These two analogs differ both in the amount of river water input and the salinity of the receiving basin. The nourishment algorithm uses a simple relationship between land loss reduction and distance from the river water introduction point combined with information on the salinity of the receiving basin based on the observations on historical land change at the two landscape analogs. However, the underlying link between increased nutrients and/or decreased salinity and increased marsh productivity has been documented. The model does not consider the routes of water distribution. In addition, the nourishment effects of diversions into brackish marshes maybe overestimated due to the interaction of sediment deposition and nourishment at the Caernarvon diversion site..

The effect of salinity reduction on land-loss (used in subprovince 4) is based on very broad assumptions (see Table C.13-4) and needs to be better developed and may be improved using the monitoring data from the CWPPRA projects where sufficient data is available.

Table C.13-4. Definition and Values of Parameters Used in Land Change Model.

Parameters	Definiton	Unit	Source	mean	st. dev.	min	max	Notes
sed load1	January total sediment load in Mississippi River	ton/month	USGS, Tarbert Landing 1949-1989	19,694,063	3,180,215	13,756,200	29,205,580	variability calculations at the decadal scale
sed load2	February total sediment load in Mississippi River	ton/month	USGS, Tarbert Landing 1949-1989	22,832,787	6,759,800	13,606,000	40,713,300	variability calculations at the decadal scale
sed load3	March total sediment load in Mississippi River	ton/month	USGS, Tarbert Landing 1949-1989	28,135,548	6,962,127	17,056,750	43,117,200	variability calculations at the decadal scale
sed load4	April total sediment load in Mississippi River	ton/month	USGS, Tarbert Landing 1949-1989	26,536,038	6,603,521	18,369,125	39,764,900	variability calculations at the decadal scale
sed load5	May total sediment load in Mississippi River	ton/month	USGS, Tarbert Landing 1949-1989	23,883,754	6,483,463	13,563,750	39,618,500	variability calculations at the decadal scale
sed load6	June total sediment load in Mississippi River	ton/month	USGS, Tarbert Landing 1949-1989	18,510,376	3,789,242	13,258,900	27,611,700	variability calculations at the decadal scale
sed load7	July total sediment load in Mississippi River	ton/month	USGS, Tarbert Landing 1949-1989	15,947,761	4,469,011	10,163,333	26,904,100	variability calculations at the decadal scale
sed load8	August total sediment load in Mississippi River	ton/month	USGS, Tarbert Landing 1949-1989	9,415,594	2,804,412	5,555,910	18,240,400	variability calculations at the decadal scale
sed load9	September total sediment load in Mississippi River	ton/month	USGS, Tarbert Landing 1949-1989	5,649,776	1,038,015	3,629,140	9,021,960	variability calculations at the decadal scale
sed load10	October total sediment load in Mississippi River	ton/month	USGS, Tarbert Landing 1949-1989	7,609,111	1,785,313	4,733,200	10,758,260	variability calculations at the decadal scale
sed load11	November total sediment load in Mississippi River	ton/month	USGS, Tarbert Landing 1949-1989	8,389,133	1,618,958	4,860,800	11,195,143	variability calculations at the decadal scale
sed load12	December total sediment load in Mississippi River	ton/month	USGS, Tarbert Landing 1949-1989	15,510,909	2,617,422	10,573,050	20,371,833	variability calculations at the decadal scale
cfs1	January average flow in Mississippi River	cfs	USGS, Tarbert Landing 1949-1989	523,983	112,439	359,729	663,688	variability calculations at the decadal scale
cfs2	February average flow in Mississippi River	cfs	USGS, Tarbert Landing 1949-1989	615,475	75,619	468,247	701,866	variability calculations at the decadal scale
cfs3	March average flow in Mississippi River	cfs	USGS, Tarbert Landing 1949-1989	697,796	39,868	584,977	747,323	variability calculations at the decadal scale
cfs4	April average flow in Mississippi River	cfs	USGS, Tarbert Landing 1949-1989	737,924	54,459	631,223	874,011	variability calculations at the decadal scale
cfs5	May average flow in Mississippi River	cfs	USGS, Tarbert Landing 1949-1989	659,471	68,191	573,591	815,602	variability calculations at the decadal scale
cfs6	June average flow in Mississippi River	cfs	USGS, Tarbert Landing 1949-1989	520,644	88,216	416,483	752,683	variability calculations at the decadal scale
cfs7	July average flow in Mississippi River	cfs	USGS, Tarbert Landing 1949-1989	378,608	40,109	308,977	458,962	variability calculations at the decadal scale
cfs8	August average flow in Mississippi River	cfs	USGS, Tarbert Landing 1949-1989	287,326	36,425	232,584	369,242	variability calculations at the decadal scale
cfs9	September average flow in Mississippi River	cfs	USGS, Tarbert Landing 1949-1989	240,417	44,361	190,913	333,461	variability calculations at the decadal scale
cfs10	October average flow in Mississippi River	cfs	USGS, Tarbert Landing 1949-1989	258,507	44,790	201,800	361,960	variability calculations at the decadal scale
cfs11	November average flow in Mississippi River	cfs	USGS, Tarbert Landing 1949-1989	300,244	73,336	219,357	449,796	variability calculations at the decadal scale
cfs12	December average flow in Mississippi River	cfs	USGS, Tarbert Landing 1949-1989	441,325	114,115	313,739	646,665	variability calculations at the decadal scale
retention	Percentage of sediments that are contained within the system	%	Based on callibration with Wax Lake Delta	15		3	20	confirmed by Majurski's (LSU thesis) estimates ranging from 3 to 20% retention
bulk density	bulk density	g/cc	Faulkner and Poach (1996)	0.835				need to find publication to see if range and st. dev. are reported
mwater	marsh water depth	m	Best professional judgement	0.5	0.1	1.5		
owater	open water depth	m	Best professional judgement	1.5	1.0	2.5		
interspersion	percentage of 1 km2 area of new land that remains as channels	%	GIS measurements of the Wax Lake Delta configuration in 1990, performed for this study	35	41	0	99	
nfresh_int	Nourishment factor 5-10 km and 15-20 km from diversion in fresh basins	%/yr	GIS measurements of the marshes east of the Atchafalaya (1956-1990), performed for this study	10	42	-164	265	based on 343 cells (1 km2)
nfresh_max	Nourishment factor 10-15 km from diversion in fresh basins	%/yr	GIS measurements of the marshes east of the Atchafalaya (1956-1990), performed for this study	21	39	-216	67	based on 159 cells (1 km2)
nbrack_int	Nourishment factor 5-10 km and 15-20 km from diversion in brackish basins	%/yr	GIS measurements of randomly selected areas in the Breton Sound estuary (1990-2001, G. Steyer unpublished data)	76		-14	221	based on 18 observations
nbrack_max	Nourishment factor 10-15 km from diversion in brackish basins	%/yr	GIS measurements of randomly selected areas in the Breton Sound estuary (1990-2001, G. Steyer unpublished data)	102		41	236	based on 13 observations

13.4.3 Sources of uncertainty in the Habitat switching module

<u>Habitat Switching Component</u>

The habitat switching module currently is restricted to four herbaceous types and one forested wetland type, this is a simplification of the extensive variety of vegetation communities described for the Louisiana coastal zone (Penfound and Hathaway 1938, O'Neil 1949, Chabreck 1972, Wharton *et al*. 1982, Sasser *et al*. 1994, Visser *et al*. 1998 and 2000). The driving forces for change were limited to salinity and inundation. Long-term datasets that include habitat type and information on driving forces are not currently available. Thus, switching between these habitat types was based on the habitat switching team's best professional judgment augmented by short-term information on salinity and inundation regimes for each of the habitat types.

The salinity data input is based on interpolations made from detailed hydrodynamic models of the open water areas. Therefore, the parameter uncertainty associated with this input can be classified as relatively high. Current hydrodynamic simulation models used in this study do not compute water levels on wetlands, due to the complexity of calculating wet and dry conditions and the lack of spatially explicit elevation data. In addition, changes in marsh elevation over time due to accretion, erosion, and subsidence are not known at a coast-wide scale. Because these data inputs are currently of such low quality, the habitat switching module was not used to change cells between land and water. The output from the land change module was used to switch cells between any of the wetland habitats and water. Switching among habitat types was based exclusively on the salinity input data. See Table C.13-5

Table C.13-5. Overview of Habitat Switching Model Uncertainty

Environmental Driver or Factor	Model Rigor	Data Source	Parameter Quality
Salinity	Low	Hydrodynamic desktop model	Low
Inundation duration*	Low	Hydrodynamic Module & elevation based on habitat type LIDAR data from Barataria Basin	Low
Inundation height*	Low	Hydrodynamic Module & elevation based on habitat type LIDAR data from Barataria Basin	Low

*Due to the low confidence in the inundation data input and model rigor, the habitat switching between any wetland type and water was driven by the results from the land change model.

<u>Wetland Primary Production Component</u>

Many factors are known to affect primary production. However, only a few of these factors are affected by restoration activities. Therefore, only salinity and inundation regimes were considered as driving forces for wetland primary production. Increased nutrient levels due to diversions of river water are indirectly captured by using the area of available wetland as a driving force. Therefore future versions of this model should consider nutrient input as a driving force. Seasonal differences in productivity are captured by running this model with a seasonal (four month) time step.

A wealth of information exists on the effects of salinity levels on the production of most of the dominant plant species along the Louisiana coastal zone, therefore the model and parameter uncertainty for this component can be classified as relatively low. This low parameter uncertainty is reflected by the relatively small standard error associated with the salinity reduction coefficients (Table C.13-5). Inundation has a significant effect on production (Conner and Day 1992, Broome *et al*. 1995, Webb and Mendelssohn 1996, Höppner 2002). However, the exact relationship among production, inundation duration, and inundation height is not clearly determined yet and the habitat switching team utilized their combined experience to describe this relationship. Therefore, the model uncertainty for both inundation-driving forces is considered high. Due to the uncertainties associated with the inundation inputs (see habitat switching component), flooding reduction was set to 0. Additional research on the effect of inundation duration on production is necessary to improve this part of the model.

Since production is a directly proportional to the wetland area available for production, the model uncertainty associated with this step is considered low. Although some data on the seasonal production of the major dominant plant species exists (Keeland and Sharitz 1995, Sasser and Gosselink 1984, Hopkinson *et al*. 1978), only a few years are represented and these data should be improved with additional years of data collection.

13.4.4 Sources of uncertainty in the Habitat Use module

The Habitat Use module provides a methodology for estimating how various restoration scenarios affect habitat capacity for key life stages of representative species of fish, shellfish, and wildlife (see Table C.13-6 and C.13-7). Habitat capacity was determined by first rating individual environmental variables (e.g., water temperature) from zero to one (quality value) in spatial cells, then the ratings of multiple factors in each spatial cell were combined to obtain a single value for each cell, and then the combined values were summed over spatial cells to obtain an overall quality-weighted habitat area for the system. The relationships between an individual environmental factor and quality were based on published laboratory and field research and previously developed Habitat Suitability Index (HSI) models. Analyses were applied on a 1-km^2 grid for each basin. Values of environmental variables were obtained as predictions from the hydrodynamic models, water quality module, and habitat switching module. A variety of species that represent the major ways coastal environments are used by fish and wildlife were analyzed. The Habitat Use module was applied to each of the basins for each of the restoration scenarios.

Habitat capacity models have a long history of use in fisheries and wildlife (see Anderson and Gutzwiller 1996). The 1996 reauthorization of the Magnuson-Stevens Act, which governs fisheries management in US coastal waters, specifically requires that fish habitat be considered in fishery management plans. The Instream Incremental Flow Methodology (IFIM) uses the habitat suitability approach to quantify how changes in river flow will affect fish habitat (Bovee et al. 1998). An approach very similar to the approach used here was recently used to quantify water quality effects on spotted seatrout in Pensacola Bay and Tampa Bay, Florida (Clark et al. 2003).

The Habitat Use module is a reasonable approach for quantifying how restoration scenarios would affect fish, shellfish, and wildlife in coastal Louisiana, and with careful implementation and interpretation the Habitat Use module provides useful information for evaluating the benefits of alternative scenarios. The major sources of uncertainty in the implementation and interpretation of the Habitat Use module are discussed below. The discussion is roughly organized around the two themes of knowledge uncertainty and natural variability, and decision uncertainty. Our discussion is not exhaustive, but rather illustrates the variety of potential sources of uncertainty that underlie Habitat Use module predictions.

The reader is to be reminded that the uncertainties discussed below should be viewed in the context that there are many certainties associated with the Habitat Use module. Because the focus here is on the uncertainties, the reader might get the wrong impression from the discussion that Habitat Use module predictions are so uncertain as to make them useless. This is not the case; we know quite a bit about fish, shellfish, and wildlife dependencies on habitat and the importance of habitat to healthy populations. The reader is urged to view the focus on the uncertainties in the proper broader context that the Habitat Use module is based on many certainties and on sound science.

Table C.13-6. Overview of Habitat Use (wildlife[a]) Model Uncertainty

Environmental Driver or Factor	Model Rigor	Data Source	Parameter Quality
Habitat type	High	Habitat Switching Module	Low
Inundation height	Low	Hydrodynamic Module & elevation based on habitat type LIDAR data from Barataria Basin	Low
Wetland Area	Moderate	Land Change Module	Low
[a]Alligator, Dabbling Duck, Mink, Muskrat, Otter			

Table C.13-7 Overview of Habitat Use (Fisheries) Model Uncertainty

Driving force or Factor	Model rigor	Data Source	Parameter quality
Salinity[a,b,c,d,e,f,g]	High	Hydrodynamic desktop model	Low
Temperature[b,c,d,f,g]	High	Hydrodynamic desktop model	Low
Wetland Area[b,c,d,f,g] / Water Area[a,e]	High	Land Change Module	Low
Water Depth[a]	High	Land Change Module	Low
[a]Atlantic Croaker, [b]Brown Shrimp, [c]Gulf Menhaden, [d]Largemouth Bass, [e]Oyster, [f]Spotted Seatrout, [g] White Shrimp			

<u>Knowledge uncertainty and natural variability</u>

The Habitat Use module is predicated on the assumption that availability of quality habitat is limiting to the populations of interest. Predicted changes in habitat may be highly precise and accurate but may not translate into changes in the number of individuals in the population. Many of the species of interest are long-lived and exhibit complex life cycles, with life stages utilizing different habitats. For example, many fish species (e.g., croaker) spawn off shore with the estuaries serving as nursery area for the juvenile life stage. The Habitat Use module assumes that more habitat for juveniles would benefit the population, whereas it is possible that individuals are not limited by nursery habitat so that more high-quality habitat could go unused by the population. One of the ultimate goals of restoration is improved populations of important species. The Habitat Use module stops the analysis at predictions of habitat quality, which contributes to the uncertainty as to whether restoration actions will actually affect populations. Furthermore, ideally it would be known how differences in habitat quality actually manifest as ecologically meaningful differences in the processes (growth, mortality, and reproduction) that affect populations. Information linking the environmental variables that dictate habitat quality to growth, mortality, and reproductive rates is sparse.

Assuming that more habitat is beneficial to the populations of interest, other factors affecting populations may swamp out any population responses to restoration scenarios. Populations of many species, and especially fish, exhibit high interannual variation due to natural variability in environmental conditions (Rose 2000). This variation in environmental conditions is often unrelated to restoration actions. Furthermore, population dynamics of harvested species are often dominated by their harvest rates, which is also outside of the influence of restoration actions. The Habitat Use module quantifies opportunities for the fish, shellfish, and wildlife to utilize more habitat, but the detection and quantification of any responses at the population level will be difficult. This results in uncertainty as to the ultimate effects of the restoration actions.

Difficulties in measuring population responses and attributing these responses to specific habitat changes lead to difficulties in corroborating (validating) the Habitat Use module. Inability to rigorously corroborate the model raises issues about uncertainty because the accuracy of model predictions is unknown. Field measurements can confirm that the restoration actions did indeed result in the assumed changes in environmental conditions (e.g., some number of acres of marsh was created). This level of confirmation relates to the validation of the Hydrodynamic model, Habitat Switching module, and Water Quality module. Corroboration of the Habitat Use module is not straightforward because habitat quality or capacity can not measured in the field other than by imposing a habitat use or related model, and it is difficult to tease out the changes in population abundances attributable to restoration actions from those due to natural variability.

There is uncertainty associated with the structure of the Habitat Use module. The Habitat Use module uses piece-wise linear relationships between environmental variables (e.g., water quality) and habitat quality (scaled from zero to one). These relationships are based on several lines of evidence. In general, the relationships between environmental variables and habitat quality are derived from laboratory studies that test the preferences and tolerances of individuals (e.g., Kostecki 1984), and from field studies that document the correlation between abundances and environmental conditions (e.g., Baltz et al. 1998). Use of the laboratory studies in the development of the relationships underlying the Habitat Use module is fairly certain. Some uncertainty arises because the laboratory studies typically examine a restricted set of environmental conditions, and typically examine tolerances to one environmental variable with other environmental variables held constant (i.e., cannot estimate interactive effects between environmental variables). The Habitat Use model assumes that the laboratory results can be interpolated and extrapolated to untested environmental conditions, and that the results apply to situations when all environmental variables vary simultaneously. The use of field data to derive the piece-wise linear relationships is uncertain because interpretation of the field data to derive the relationships is based on correlative, not cause and effect, analysis. The assumption is that higher densities measured in the field at some environmental conditions implies those environmental conditions are good habitat. Additionally the histories of the individuals caught in the field are unknown, and whether differences in environmental conditions at their time of capture accurately reflect their preferences and tolerances.

At the finer level of the mechanics of the Habitat Use module there are several major sources of uncertainty. The habitat suitability approach that underlies the Habitat Use model is clearly a simplification of complex situation. Analyses are limited to a few of the environmental variables, which imply that some potentially important environmental variables could be missing. Examples of potentially important missing variables in the present implementation of the Habitat Use module include turbidity and the amount of edge (intersection of water and vegetation), both of which are known to be important for some of the species analyzed (Chesney et al. 2000; Minello et al. 1994).

Given the major environmental determinants or correlates to habitat quality have been captured, there is uncertainty associated in how these multiple environmental variables are combined into a single measure of habitat quality. The standard techniques (geometric and arithmetic averaging) were used in the current implementation of the Habitat Use module, but the decisions about how to average influence the relative importance of the different environmental variables to the final prediction of habitat quality How we combine over multiple environmental variables implicitly determines the importance we assign to different environmental variables, and can influence how responsive our predictions of habitat quality are to variation in some environmental variables over others.

A potentially large source of uncertainty is the fact that the inputs to the Habitat Use module are predictions from the other models. Thus, Habitat Use module predictions are subject to uncertainty simply because there is uncertainty associated with the inputs to the Habitat Use module. The Habitat Use module could be absolutely correct but still produce highly uncertain predictions due to the uncertainty in the predictions from the other models. The uncertainties associated with the other models propagate, and potentially accumulate, as predictions from one model are passed as inputs to the next model. The Habitat Use module is the final ecological model in the chain, and thus receives inputs that have themselves accumulated potentially large uncertainties and whose predictions are based on their own suite of assumptions.   Also, because the Habitat Use module used predictions from other models as inputs, the spatial and temporal scale of the Habitat Use module was dictated by the scales of the other models. Both the temporal (roughly monthly) and spatial (km^2) resolution of the Habitat Use module are too coarse for many of the species of interest, and thus contribute to the uncertainty of Habitat Use module predictions. There is also uncertainty associated with Habitat Use module predictions because it is assumed that only restoration actions would affect the environment in the future. For example, the possible effects of global climate change were not incorporated into model forecasts. It is conceivable that the most important environmental changes to affect species will be climate change, unrelated to restoration actions.

Decision Uncertainty

A final source of uncertainty is the potential for misinterpretation of the predictions from the Habitat Use module. Users of model results can wrongly infer predicted changes in habitat capacity as expected changes in populations. Users can also misinterpret model predictions because of erroneous beliefs about the uncertainty associated with model predictions. On one hand, users might wrongly attribute too much accuracy and precision to Habitat Use module predictions, and infer differences between restoration scenarios when no differences exist and have false expectations about measuring and observing large responses in the field. On the other hand, users might digest all of the sources of uncertainty associated with the Habitat Use module and wrongly conclude that model predictions tell us nothing. Both of these extreme situations are wrong and both lead to misinterpretation of model predictions. Quantifying the uncertainty associated with Habitat Use module predictions is critical to ensure predictions are properly interpreted.

13.4.5 Uncertainty in Hydrodynamic Models

Since all the hydrodynamic models are numeric models, uncertainty in model output is mostly related to model calibration and validation. Table C.13-8 provides an overview of the hydrodynamic model uncertainty. These issues are explained in each of the chapters discussing model development and implementation. For specific information in hydrodynamic model structures see Chapters 3 (Subprovince 1), 4 (Subprovince 2), 5 (Subprovince 3) and 6

(Subprovince 4). Below are some of the most critical model limitations and associated uncertainty described in those chapters.

Table C.13-8 Overview of Hydrodynamic Model Uncertainty

Environmental Driver or Factor	Model Rigor	Data Source	Parameter Quality
Wetland Elevations	Moderate	Field surveys, engineering firms, LIDAR,	Low
Bathymetry	Moderate	Field surveys, engineering firms, NOAA geodetic,	Low
Meterology	Moderate	State and airport stations, LUMCON, oil platforms,	Moderate
Tides	Moderate	NOAA, LUMCON/University studies, DNR, USGS, COE	Moderate
Water Flow Fields	Moderate	NOAA, LUMCON/University studies, DNR, USGS, COE	Low
Salinity	Moderate	NOAA, LUMCON/University studies, DNR, USGS, COE	Moderate
Suspended Sediment	Moderate	NOAA, LUMCON/University studies, DNR, USGS, COE	Moderate

Subprovince 1 (The Princeton Ocean Model-POM) (From Chapter 3, McCorquodale and Georgiou 2003).

"The model was not calibrated for large flows through a channel, such as the ones used in the different restoration scenarios. Data from such large flows are generally unavailable. Furthermore, there is an error associated with large flows restricted through a non-eroding channel as POM does not have wetting and drying algorithms, or sediment transport. These model limitations are being evaluated in several research projects that have been funded to improve model development for coastal restoration. A subroutine for wetting and drying wetlands coupled with forcings from coastal channels has been developed on another research project looking at wetland hydrology (Meselhe and Twilley, unpublished).

1 POM uses the hydrostatic assumption for pressure variation with depth.
2 The use of a sigma coordinate system requires that the variations in bed elevations be small. The model limitation is 20% bottom slope; however, even this may result in pressure gradient errors that affect the movement of external and internal waves. The large sigma gradients also affect the transport of mass in the system. This can lead to an underestimation of the saltwater intrusion into a shelf with steep bathymetry. For practical computation reasons the number of sigma layer was limited to 10 with surface and bottom refinement. A sensitivity study was conducted to determine that this was an adequate number of layers.
3 POM is limited to orthogonal grids. This makes it difficult to fit complex boundaries and narrow tributaries or passes. To accommodate this limitation it was necessary to adjust the depth and/or the roughness in some passes or channels to ensure that the hydraulic capacity is well represented. This leads to local errors in the solution in and near these elements.
4 All models should be validated. The POM used in this study has not been fully validated. Inter-model comparisons have been made with the depth averaged solutions obtained by

RMA2/RMA4. There is general agreement of the depth averaged circulation patterns and the salinity distribution.

5 All model are subject to uncertainty. Based on comparisons with a typical (10 year average) salinity distribution in the Pontchartrain Estuary, POM had a annual error in salinity of the order of +/- 1 ppt in the upper and middle regions and +/- 2 ppt in the lower regions or about 25% uncertainty. The relative predictions for the different scenarios with respect to the base, were subject to similar uncertainty. Nevertheless, the final calibrated model appeared to predict the direction of any trend.

6 The POM was used to make a rough estimate of the distribution of dissolved inorganic nitrogen (DIN) in the plumes of the diverted Mississippi River water. These plumes were consistent with the zones of Lake Pontchartrain where historical algal blooms have been observed after the opening of the Bonnet Carré Spillway. The DIN submodel was calibrated with the 1997 Bonnet Carré data.

7 Georgiou (2002) conducted sensitivity studies on bed roughness in POM for Lake Pontchartrain. The bed roughness of 2 cm that was used in this study were based on this sensitivity analyses. Local adjustments in roughness were made to avoid unrealistic heads in the large diversion.

8 POM does not have an explicit wetting and drying algorithm. The flooding of marshes was simulated by slightly lowering the marsh and compensating for this by increasing the frictional resistance. Flooding was based on the depth above the original marsh. This is an aspect of the model that needs improvement.

9 POM was very sensitive to ‘spikes’ in wind velocity. This problem was avoided by using 6-hour magnitude and direction averaged wind inputs.

10 There are residual errors due to the assumed initial conditions. Due to the long hydraulic detention time, of several months depending on the tributary flows, in the Pontchartrain Estuary, the initial conditions for a one year simulation can influence the solution for several months. This was partially corrected by using the December results for some trial runs as initial conditions for the final runs; nevertheless, this did have an influence on the predictions of some scenarios where there was a carry-over from the diversions of one year to the starting conditions for the next year. A simple cell model was used as an aid to improve the initial conditions for the three scenarios.

POM is generally 2nd order accurate. It has an explicit external model for the gravity wave component. The second order scheme often produces unrealistic oscillation in the free surface and the transported variables. This can be overcome by upwinding; however, the use some schemes such as the 5-node 1st order upwind schemes introduces artificial diffusion. This can mask the real diffusion. These schemes can be combined with anti-diffusivity terms to over-come the stability or oscillation problems with adding excessive artificial diffusion. The temperature and salinity in the POM were run by a 2nd order scheme. Some ‘rippling’ and ‘cluster’ instabilities were noted in the results if the time step was increased beyond a critical limit. To complicate the problem, this time step limit was strongly dependent on the wind shear”.

Table C.13-9. Definition and Values of Parameters used in the Princeton Ocean Model

Parameters	Definiton	Unit	Values (or range)	Source
Dt	Time step	seconds	0.5 - 2	Selected for Stable Solution
H	Model Bathymetry	m	(+0.5) - (-20)	Digitized NOAA Navigation Chart and COE Storm Surge Model Bathymetry
K_{DIN1}	Dissolved Inorganic Nitrogen Decay/Uptake Rate (high Concentration rate)	/hour	0.0185	1997 Bonnet Carre Opening Field Data
K_{DIN2}	Dissolved Inorganic Nitrogen Decay/Uptake Rate (low Concentration rate)	/hour	K_{DIN1} / 10	1997 Bonnet Carre Opening Field Data
K_{DIN3}	Dissolved Inorganic Nitrogen Decay/Uptake Rate (marsh/shallow water uptake)	/hour	K_{DIN1} X 2	best estimate
Kh	Horizontal diffusion coefficient	m^2/s	Function of Velocity Gradients and grid size	Mellor Yamada, 1982
Kv	Vertical diffusion coefficient	m^2/s	Function of Velocity Gradients and grid size	Mellor Yamada, 1982
HORCON	Horizontal mixing coefficient	n/a	0.3	Lake Pontchartrain Calibration; Smagorinsky Formulation
–	Density	kg/m3	Function of Temperature and Salinity	Equation of State
TPRNI	Inverse Turbulent Prandtl Number; diffusivity to momentum transfer	dimensionless	0.1	Lake Pontchartrain Calibration
Dx	grid dimension (x - direction)	m	650 - 900	n/a
Dy	grid dimension (y - direction)	m	300 - 2000	n/a
WU;WV	Wind Stress	$dynes/cm^2$		1996 record from Lake Pontchartrain Midlake Station
Q	River Discharge	cfs	0 - 15,000	USGS Gauge Stations; 10 year daily averaged flow

Subprovince 3 (ABM-Acadiana Basin Model) (From Chapter 5, Reyes et al 2003).

“The accuracy of Acadiana Basin Model (ABM) model functioning and predictions could be improved with better input and validation data. For example, elevation is one of the most sensitive parameters affecting marsh survival. However, accurate elevation data exist for only a few locations. Extensive monitoring of salinity and water level would also allow much better calibration and validation of the model. See Table C.13-10 for a definition of the variables used in the ABM.

Results suggest that the current Atchafalaya discharge affects marsh sustainability within a radius of 19 to 31 miles (30 to 50 km), depending on the intervening topography. The ABM predicted that Marsh Island, separated by 50 km of bay from the source, would lose land at a rate of - 0.5% per year if river discharge was halved. This is similar to the loss rate that prevailed for the 1956-90 hind cast period for western Terrebonne marshes more than 22 mi (35 km) from the deltas (-0.4 to -0.6% per year). These were presumed to lie outside the influence of the river. Marshes at greater distances to the west on the eastern margin of the chenier plain experience far lower historical loss rates, so the effect of the river is more difficult to detect.

Loss rate diminishes as river influence grows, whether this is due to an increase in discharge or a decrease in distance from the source. But not all areas within the ABM domain are equally susceptible to loss. Averaging predicted loss rates from all sub-areas outside of the deltas permits extrapolation to a base rate, without the river, of - 0.285 percent per year 2.36 ft^2 $-y^{-1}$ (6.11 km^2 y^{-1}). Deviation from this base, then, can be used to scale the effects of the river over the ABM domain.

The ecological module simulated plant growth conditions that were represented as a series of habitat maps for the ABM area. The agreement between the two maps was assessed with a goodness-of-fit spatial statistics routine that compares the spatial pattern of habitat cells at multiple resolutions (Costanza 1989), which returned a value of 94.9 out of a possible 100 (Martin 2000). The multiple resolution approach allows a more complete analysis of the way in which the spatial patterns match (Day et al. 2000, Turner 1997, Turner 2001). All six habitat types of the ABM were accounted for in the calibration and validation procedures. The BTELSS returned values of 89.3 and 74.4 for calibration and validation simulations, respectively (Reyes et al. 2000, Reyes et al. 1998). Further calibration and validation of the models included comparing predicted habitat trends with historical rates of change and comparing recorded and predicted salinity and suspended sediment concentrations at specific locations.

The ecological and habitat switching modules of the ABM focused on those factors that directly and predictably influence land elevation and habitat type. Among the most important factors for vegetation production is nutrient availability. The influence of river-borne nutrients can not be distinguished from the effects of freshwater and sediment when examined in a landscape context. This lack of watershed nutrient information made it difficult to predict availability, rates of transformations within the estuary, or exchange with the atmosphere, much less the response of plant communities to all of these factors. While nutrient influences affect land elevation, inclusion of nutrients would required an extensive and comprehensive field monitoring effort perhaps at a prohibitively cost. The productivity module of the ABM should include nutrient influences to make the model a more realistic tool in predicting eutrophication and wetland nutrient cycling”.

Table C.13-10. Definition and Values of Parameters used in the Acadiana Basin Model.

Parameters	Definiton	Unit	Values (or range)	Source
area	area of wetland and aquatic habitats	km2		Reed 1995- based on US Fish and Wildlife Service map
	classified wetland area	km2		aggregated to 1 Km2 from 625 m2 USFWS
	rainfall			National Weather Service from 3 locations within domain
	pumping from developed areas			parishes and water districts
	salinity (barataria)	kg/m3	calculated	LDWF from Grand Terre Laboratory
	salinity (Terrebonne)	kg/m3	calculated	LDWF monthly (pers.com), Murray and Donley 1994
	riverine inputs (Atchafalaya river)	m3/s		USACOE New Orleans District Simmesport, Tabert landing
	evaporation	m/d		Southern Regional Climate Center
	wind direction	m-s-1		Southern Regional Climate Center
	temperature	degrees C		National Weather Service from New Orleans Airport
	wind velocity	m/s		canonical correlation of data from 1964 used for years 1955-1963; real data from 1964 to present
	wind stress	N/m2	calculated x, y	calculated in model from 10 m vel.
	tide			National Ocean Service at Bayou Rigard, Grand Isle for 1955-1979; East Point, Grand Isle, from 1980-1988
	eddy diffusion coefficient			
	Manning's roughness			variable by habitat type, channel size
	land elevation	m	calculated	initial Alawady and Al-Taha 1996 from 1994 survey map
	suspended sediment	kg/m3	calculated	Booth et al.
	water height	m	calculated	
	subsidence	m/y	input parameter .05 -[illegible]	specified for entire domain
	sedimentation	m		Yeh and Chou 1979
	relative sea-level rise	cm/yr	0.5	Reed 1995
	relative sea-level rise (1975-1992)	cm/yr	1.19	long term trend
	water velocity	m/s		Cassuli 1992
	bed shear stress due to waves and currents			Yang 1996, Grant and Madsen
	resuspension of sediments	kg/s		Vanoni 1977, Yang 1996, Martin 2000, Booth et al. 2001
	particle size	mm	0.014	Morgan 1970
	settling velocity	m/s	0.00033	Dietrich 1982
	wetland type	category	swamp, fresh, interme[illegible]	[illegible] al 1987; Tiner 1993; Visser et al 1996
	belowground biomass	kgOM/m2		Swanson and Thurlow 1973; Trahn 1982;Penland and Ramsey 1990
	aboveground biomass	kgOM/m2		
	salinity thresholds for marsh types			Swanson and Thurlow 1973; Trahn 1982;Penland and Ramsey 1990
	respiration rates			
	excess fixed carbon			
	storage of inorganic sediments	kg/m2		Chmura et al 1992
	dead belowground organic sediments			
	inorganic bulk density	g/cm3	2.65	Chabreck 1972; Conner et al 1987; Tiner 1993; Visser et al 1996
	organic bulk density	g/cm3	1.14	Nyman
	pore-space volume		90%	Gosselink, Nyman
	salinity (freshwater marsh)	ppt	0-<4.5	Howes et al 1986; Pezeshki et al 1987
	salinity (swamp)	ppt	0-9.0	Pomeroy et al 1976;Cronk and Mitsch 1994; Dai and Wiegert 1996
	salinity (brackish marsh)	ppt	4.5-<12.5	Gosselink and Kirby 1974; Howes et al 1985
	salinity (saltwater marsh)	ppt	12.5-40	
	Biomass (freshwater)	kgOM/m2	0.9-4.6	
	Biomass (swamp)	kgOM/m2	20.3-45.2	
	Biomass (brackish swamp)	kgOM/m2	0.4-2.2	
	Biomass (saltwater marsh)	kgOM/m2	1.2-6.0	Nyman et al 1990

Subprovince 4 (H3D, dimensional hydrodynamic and advection dispersion model) (From Chapter 6, Meselhe 2003).

"This model suffers from two major limitations: a) the marsh area between the Sabine Pass and Calcasieu Lake was not included in the model domain and b) the southern boundary of the model stopped at the Sabine and Calcasieu passes which made it difficult to model any suggested alterations that are close to the existing boundary. To reduce uncertainties in model output further development is needed once surveys are conducted to obtain accurate and detailed marsh surface elevations. While several survey reports have been written (e.g. Louisiana Coastal Wetlands Conservation and Restoration Task Force, 2002; Gosselink et al., 1979), no comprehensive sediment and water budget has been developed for this region. Even the connection between region 4 and the eastern regions of the coast has not been established. An overall computer model is needed to understand the hydrologic characteristics and the linkage between hydrology and ecology in region 4. This model should quantify evaporation, evapotranspiration, fresh water inflow, tidal prism, salinity intrusion, and precipitation. The model should be capable of describing the details of the flow and salinity patterns, including marsh inundation. Quantifying the frequency and duration of the marsh inundation is crucial to the restoration effort of Region 4".

13.4.6 Propagation of Uncertainties in the LCA Modules

In the *LCA* model, the different hydrodynamic, water quality, ecological, and habitat modules are used in sequential manner. This situation is illustrated schematically in Figure C.13-4. A summary of the list of parameters and input/output variables in the *LCA* model is given in Table C.13-11 that illustrates the complexity of the flow of information though the different modules. For example, predictions of salinity, water level, and sedimentation rates are provided by the hydrodynamic modules and then passed as input variables to the land building, habitat switching, water quality and habitat use modules. Also, information about land water ratios are predicted by the land building modules and then used to drive the habitat use and habitat switching modules. Given such multiple levels of information exchange and interaction, it is expected that errors and uncertainties will propagate through this sequence of modules. Therefore, there is a need to estimate the combined effects of these uncertainties on the assessment of final model outcome or any derived benefits and performance targets.

Within each of the modules we identified issues that have implications in the comparison of alternate restoration scenarios. For land change, high discharge scenarios are more sensitive to errors in the sediment load parameter than low discharge scenarios. In contrast, low discharge scenarios are more sensitive to errors in the nourishment assumption than high discharge scenarios, due to the relative contribution of the nourishment component to overall land change. For hydrodynamics, the box models are less adequate in reflecting the salinity gradient in high discharge scenarios than in low discharge scenarios. This representation of the salinity gradient is propagated in the habitat switching module and the habitat use modules. In the habitat switching module this results in the under estimation of saline habitats in high discharge scenarios, while in the habitat use model this results in an under estimation of high salinity species and an over estimation of moderate salinity species. Nutrients are currently only removed in the box adjacent to the diversion structure in the water quality module underestimating nutrient removal in the high discharge scenarios, while low discharge scenarios are less affected by this assumption. Low discharge scenarios probably over estimate production, because loading rates are outside the range of data used to fit the removal curve. The water quality module estimates of nutrient removal are most sensitive to errors in residence time which is calculated based on the salinity results from the hydrodynamic module.

The propagation of uncertainty through the modules is ultimately expressed in the benefit calculations (see Chapter C.12). Those benefit protocols that rely heavily on inputs from the habitat productivity and habitat use modules (B1, B2, B5 and B6) have a larger uncertainty associated with them because of propagation of uncertainties than those benefits numbers that dependent on land change and water quality (B3 and B4).

Analysis on model error propagation can be conducted and using simulation techniques such as the Monte Carlo simulation approach (e.g., Reckhow and Chapra, 1983; Loucks and Stedinger, 1994). However, as discussed in Lall et al., (2002), error propagation analyses that are based on assumption of independence among the uncertain variables and parameters may lead to either overestimates or underestimates of the overall combined model uncertainty. Therefore, information about covariance functions for the different interacting model variables should be integrated in any analyses on propagation of uncertainties within the *LCA* modules.

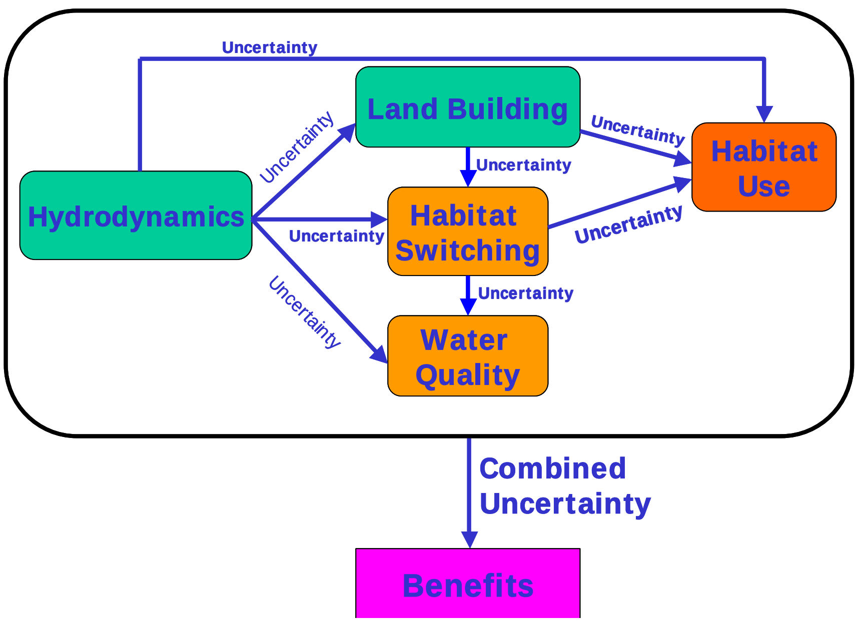

Figure C.13-4 Schematic diagram showing exchange of information and associated uncertainties across the LCA modules.

Table C.13-11 Module variables and interactions among modules.

	Module				
Variable	Hydro-dynamics	Land Change	Water Quality	Habitat Switching	Habitat Use
Wind speed and direction	Input				
Initial water level	Input				
Initial salinity	Input	Input[1]			
Initial temperature	Input				
River temperature	Input				
Historical land change rates		Input			
River sediment load		Input			
Sediment retention factor		Input			
Bulk density of deltaic soils		Input			
Initial land area	Input	Input			
Bathymetry	Input	Input	Input		
Land elevation	Input	Input	Input	Input	Input
Diversion flows	Input	Input	Input		
River Nitrogen			Input		
Nourishment factor	Output[1]	Input			
Salinity	Output.		Input	Input	Input
Water level	Output		Input	Input	Input
Water residence time	Output		Input		
Water temperature	Output		Input		Input
Wetland area		Output	Input	Input	Input
Habitat type				Output	Input
Nitrogen removal			Output		
Water primary production			Output		
Wetland primary production				Output	
Chlorophyll a Water Column					
Habitat quality alligator,					Output
Habitat quality dabbling duck					Output
Habitat quality mink					Output
Habitat quality muskrat					Output
Habitat quality otter					Output
Habitat quality Atlantic croaker					Output
Habitat quality brown shrimp					Output
Habitat quality gulf menhaden					Output
Habitat quality largemouth bass					Output
Habitat quality oyster					Output
Habitat quality spotted seatrout					Output
Habitat quality white shrimp					Output

[1]In sub-provinces 1, 2, and 3, the nourishment factor is based on the initial salinity of the receiving basin. In province 4, the nourishment factor is based on the change in salinity relative to the no action scenario.

13.5 Validation of the CLEAR Modules

Due to the model structure and current development of the water quality, habitat switching, land change, and habitat use modules, there are not validations of these models. Model validations for these modules will need to be performed as more data related to parameter estimation is obtained. In the case of the hydrodynamic models some validation has been performed. Specific details are described in Chapters C.3-6.

13.6 Uncertainty in Performance Measures

Performance measures are specific variables or characteristics of the natural system that quantitatively identify and describe the restoration targets (Zedler, 2001). Most monitoring plans fail because performance measures selected try to do too much within their resources (human and budget resources), or lack connection back to design of restoration goals, and therefore result in ineffective evaluations. The challenge in restoration monitoring is deciding which attributes of ecosystems to monitor, and to determine which of the changes in attributes observed represent significant departures from expected natural variability (Twilley and Rivera-Monroy, in press).

There are several criteria for selecting endpoints and performance measures in a restoration program. The initial selection process is based on the conceptual models that describe how causal mechanisms associated with ecosystem degradation are linked to proposed restoration alternatives. As such, performance measures provide two important functions: (1) they represent information that describe the patterns of ecosystem structure and function over time documenting restoration trajectories; and (2) they track changes in processes that document mechanisms linked to conceptual models of how ecosystems work. The former utility of performance measures is to document the effectiveness of restoration alternatives (patterns); the latter is to test the assumptions as to what stressors are associated with system degradation (mechanisms) variability (Twilley and Rivera-Monroy, in press).

Targets are important ecosystem attributes that provide the link between the program or project goals/objectives and the performance measures (Stayer et al. 2004). Currently, the alternative formulation for the LCA study has been based on two ecosystem objectives: 1) increase land-water ratios, enhance connectivity and material exchanges to improve productivity and sustain diverse fish and wildlife habitats, and 2) reduce nutrient delivery to the shelf by routing Mississippi River waters through estuarine basins (Hawes et al. 2003). Based on these objectives, performance measures need to be developed to cover the specific spatial and temporal characteristics of the restoration projects planned for each of the four sub-provinces considered within the LCA program..

13.7 Recommendations on Future Uncertainty Analyses for the LCA Ecosystem Model

The preliminary analysis conducted in this study has indicated the necessity and the critical need for addressing and analyzing the uncertainty associated with the predictions of the LCA ecosystem model. This will provide decision-makers with information necessary to quantitatively assess the likelihood that a certain restoration project will meet a pre-specified performance target. A complete uncertainty analysis usually involves several components such as:

- Identification of all sources of uncertainty that contribute to probability distributions of each input or output variable
- Specification of marginal and joint probability distributions of input variables and parameters
- Propagating these uncertainties through the different modules
- Constructing probability distributions of model outputs and the associated performance measures